Population Health Metrics

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The role of education composition in shaping the burden of obesity and diabetes in Indonesia: a microsimulation-based projection study

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Abstract

Background Diabetes prevalence is increasing worldwide, particularly in developing countries and disadvantaged groups. Alongside this phenomenon, the expansion of educational attainment has led to changes in population educational composition, which can significantly influence social disparities in diabetes and its risk factors, including obesity. This paper explores the role of changing educational composition in shaping the future burden of excess body weight and diabetes in Indonesia, a country with a rapidly growing prevalence of both diabetes and obesity.

Methods We utilise three data sources as the inputs for our projection model. Panel data from the Indonesia Family Life Survey (IFLS) for 2007 and 2014 were used to compute health transition probabilities by age, sex, and education status using a multinomial logit model. Results from a dried blood test were used to adjust for undiagnosed diabetes in the projection model. The Indonesian National Health Surveys (Riskesdas) in 2007, 2013, and 2018 were used to estimate the prevalence of excess body weight and diabetes by age, sex, and education. Finally, we used projections of Indonesia's population size and composition by age, sex and education level for the period 2010 to 2060 from the Wittgenstein Centre Human Capital Data Explorer version WIC2018 v2. We employ a cohort component model with microsimulation to project the population forward.

Results The estimated prevalence of diabetes from our projection model incorporating population education composition is 7.8% in 2010 and is expected to reach 16.7% by 2060. The most rapid increase in prevalence (14% growth in 50 years) is estimated among people with primary education, while other groups show smaller rises.

Conclusion Incorporating population educational composition into projections of the burden of excess body weight and diabetes provides valuable insights into social disparities in diabetes over time. This can inform policy decisions by helping to prioritise healthcare budgets, targeted disease prevention programs, and diabetes treatment for high-risk groups based on educational status.

Keywords Diabetes, Obesity, Education, Projection

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Introduction

Diabetes is one of the most rapidly growing chronic diseases in the world and has been described as "the disease of the 21st century" [1]. An estimated 529 million people were living with type 1 and type 2 diabetes in 2021, and these numbers are expected to increase up to 1.3 billion by 2050 [2]. Increases in body mass index (BMI) and the growth of aging populations are accelerating the rise in diabetes prevalence globally [2, 3]. Low and Middle-Income Countries (LMICs) are most affected by this global rise in diabetes, and are home to 80% of the global adult population living with diabetes [4]. These rising trends in diabetes prevalence and its comorbidities pose significant challenges to national health systems and sustainable economic development.

In this paper, we focus on understanding future trends in diabetes in Indonesia, a country experiencing both a rapid rise in overweight/obesity and a rapid change in population education composition. Indonesia is the fourth most populous country in the world with over 280 million people. The country is in the global top ten for the number of people living with diabetes, and over 70% individuals with diabetes are undiagnosed [4]. The International Diabetes Federation projected that the burden of diabetes in the country will be 11.7% by 2045 [5]. However, this burden appears to have risen more rapidly than anticipated, and the Indonesia National Health Survey found that the prevalence of diabetes among adults aged 15 years and older increased from 10.9% in 2018 to 11.7% in 2023 [6]. Alongside these rapid changes in BMI and diabetes, Indonesia has experienced a rapid increase in educational attainment across cohorts. However, the combined implications of growing educational attainment, shifts in diabetes risk factors, and changes in diabetes prevalence for Indonesia's future population have not yet been explored in this context.

Social disparities of diabetes and its implications

Social and environmental factors are some of the most essential health determinants, alongside individuals' health-related behaviours and the health care system [7]. A substantial fraction of differences in health outcomes are attributed to the social determinants of health [7]. In the case of prediabetes and diabetes, social and environmental factors shape a differential in risk factors, resulting in a disproportionate burden of diseases, economic cost, and adverse diabetes outcomes among disadvantaged groups [8, 9].

Previous literature has demonstrated the important role of socioeconomic status in shaping social disparities of diabetes in the population. The prevalence of diabetes and related risk factors are highest among women from low socioeconomic status as compared to higher socioeconomic groups, but the socioeconomic gradient is less consistent in men [8, 10, 11]. Individual's low socioeconomic status combined with low capacity of the health system for diagnosis and limited public awareness of diabetes contributes to a large proportion of undiagnosed diabetes in LMICs, which is exacerbated among disadvantaged groups within these populations [4, 12]. Differentials in education, income and occupation affect social disparities in access to diabetes care and quality of treatments, in ways that can increase the risk of complications and premature mortality in low socioeconomic status groups [8, 12, 13]. Moreover, literacy level is an essential factor in successful diabetes self-management and diabetes education delivery [12]. Literacy-sensitive interventions can improve knowledge and effective diabetes self-management, especially among ethnic minority and low-educated group [8, 14, 15]. This evidence highlights the important role of socioeconomic status in shaping social disparities of diabetes, and the potential to take a targeted approach for public health promotion, prevention and intervention programs to address the growth of diabetes in the population.

Diabetes can have substantial economic costs to disadvantaged groups. Individuals with diabetes require long-term treatment, which is very costly and can burden health systems regardless of the level of economic development and individual's economic condition [16]. The global economic cost of diabetes was estimated at US$1.3 trillion in 2015, and is projected to reach $2.2 by 2030, accounting for 1.8% of global gross domestic product if present diabetes trends continue [16]. Without equal capability and opportunity to avoid the risk factors for diabetes onset, receiving a diagnosis, and accessing diabetes treatment, the rise in diabetes prevalence can exacerbate the deprivation of lower socioeconomic status groups. A study among Medicare beneficiaries in the US showed a larger burden of out-of-pocket spending for diabetes care among lower income groups compared to higher income groups [17]. The burden out-of-pocket payment can be larger for people with diabetes living in LMICs that have low funded health systems and no universal health coverage [18]. Furthermore, labour participation of adults living with diabetes is lower than among people without diabetes, which can increase the risk of falling into income and multidimensional poverty among people with diabetes [19, 20].

Considering the disproportionate distribution of risk factors for diabetes, diabetes prevalence, diabetes related complications, and the economic implications of the disease for disadvantaged groups, estimating and projecting social pattern of the disease is necessary to inform policy makers. The projection of the social pattern of the disease in populations can inform a targeted-group approach for funding health systems and diabetes prevention and treatment programs to improve health equality for the entire population. In addition, simulation on the effect of targeted diabetes prevention policies by accounting socio-economic disadvantaged indicators may provide insightful evidence for policy maker on the cost-effectiveness of targeted policies for disadvantaged groups [21]. Hence, these approaches in planning health interventions may reduce inequalities in diabetes related risk factors, health screening provision, and diabetes care services in populations. These targeted group intervention can reduce health inequalities and prevent the adverse effects of diabetes among disadvantaged groups with high risk of diabetes.

Projecting social disparities in the burden of diabetes

Recent estimations and projections of the global and national burden of diabetes at regional and national level have begun to incorporate countries' Socio-demographic Index (SDI) into the projection model [2, 22]. The SDI is a composite index of average income per capita, mean years of schooling population aged 15 years or older, and total fertility rate reflecting socio-demographic development of the country [22, 23]. However, rapid educational development globally, and especially in LMICs countries, has resulted in significant changes in educational opportunities across generations. This educational development manifests in marked changes in population education composition, with a substantial gradient in education structure across birth cohorts.

The population education composition is worth exploring for better understanding its implications for the current and future social patterning of diabetes. Increased educational attainment can improve life expectancy and lead to better health outcomes [24, 25]. Further, improvements in the population level of education can act to both widen and narrow socioeconomic gaps in health disparities, depending on a countries' level of economic development [26, 27]. The ongoing nutritional transition and rapid economic development in LMICs, combined with rapid expansion of mass education, creates a unique scenario for studying how education and health interact to shape disease patterns at present and in the future [28]. Our research offers a novel approach to estimating and projecting the burden of diabetes in adults by taking into account both changes in the population's education composition and trends in overweight/obesity.

Indonesian context

Building from previous literature from the Indonesian population and incorporating demographic changes, this study focuses on understanding how changes in educational composition may impact the future burden of diabetes in the country. Previous literature has documented sex differentials in individual body mass index trajectory over life span, with rapid rises and higher BMI in early adulthood in women compared to men [29]. Considering differentials in birth cohorts, younger Indonesians have higher mean BMI compared to older generations [29]. Education plays an essential role in shaping the social patterning of obesity between the sexes and across generations over time [29]. Indeed, previous research has also identified the causal effect of education on excess body weight in the population [30]. Recent evidence demonstrated the heterogeneity in the consequences of body mass index trajectories on diabetes in later life by sex and education status [10]. This existing evidence highlights the role of education in shaping obesity and diabetes risk in the Indonesian population, and motivates our analyses projecting these burdens into the future by age, sex, and educational attainment. Incorporating advances in educational attainment as an attribute of the quality of human capital of a population can improve health projections and potentially provide a more accurate representation of population health in the future, as populations both age and grow more educated in the coming years [31, 32].

Data sources

This study exploits three data sources to develop health transition probabilities, obtain disease prevalences, and measure the baseline demographic and educational characteristics in Indonesia. The first dataset is the longitudinal Indonesian Family Life Survey (IFLS). Our analyses use the most recent two waves of the survey (2007 and 2014) where detailed health measurements were collected. IFLS collects information on individuals social and demographic characteristics, and also conducts health measurements, including body height and weight, used to calculate body mass index (BMI). We classified individuals with BMI of greater than or equal to $23\ \mathrm{kg/m^2}$as overweight, following Asian-Pacific population BMI cut-offs [33]. The study also gathered information on whether an individual had been diagnosed with diabetes by a medical professional, and in 2014 collected dried blood tests used for diabetes diagnosis based on HbA1c levels. Individuals were classified as diabetic if they had an HbA1c level of greater than or equal to 6.5% [34], or reported a previous physician diagnosis of diabetes. This information is used to calculate the transition probability matrix of health status by age, sex, and education level. The transition probability matrix contains estimates of the transition rates between the four modelled health outcomes: "neither overweight nor diabetic", "overweight without diabetes", "diagnosed with diabetes", and "mortality". In total 21,296 individuals aged 25 and older are included in this analysis with information on sex, education level, health measures, self-reported diabetes, and/or HbA1c measured. Sample selection is in the appendix Figure S1.

Second, we use data from a repeated cross-sectional study on health in Indonesia, the Indonesian National Basic Health Survey (Riskesdas) conducted in 2007, 2013, and 2018 to estimate the prevalence of "neither overweight nor diabetic", "overweight without diabetes", and "diagnosed with diabetes" in the population aged 25 and older. Riskesdas was used to estimate the prevalence of excess weight based on objective measurement of individual body weight and height. In addition, Riskesdas also collects information on self-reported diabetes diagnosed by health practitioners to estimate the prevalence of diabetes in the population by sex, age, and education level. In total, there were 490,144 individual samples in 2007; 546,660 in 2013; and 488,966 in 2018 included in this analysis. Considering the large proportion of undiagnosed diabetes in Indonesia, the prevalence of diabetes is adjusted based on estimated probability of having undiagnosed diabetes by age, sex and education level. Information on diabetes diagnosis from the HbA1c values of IFLS is used to adjust the prevalence of undiagnosed across population groups.

Finally, the population baseline for projection was obtained from the Wittgenstein Centre Human Capital Data Explorer version WIC2018 v2. The data is publicly available and accessible in the https://dataexplorer.wittgensteincentre.org/wcde-v2/. The data source provides detailed information on the population of Indonesia, including population size and composition by age, sex and education level for the period 2010 until 2060. We use population data based on the Medium (SPP2) scenario. The SPP2 scenario is based on medium fertility, mortality, migration and education development scenario following the Global Education Trend (GET) [35].

Transition probability matrix

This study employs several analytical methods to produce the inputs for the projection. We first estimate the health transition probabilities from IFLS data using a multinominal logit model. Figure 1 illustrates transition probability in this study. The $i1$ donates the state of "neither overweight nor diabetic", $i2$ donates the state of "overweight without diabetes", $i3$ donates the state of "diagnosed with diabetes", and $i4$ donates to death. The arrows illustrate the direction of possible transitions from time 0 (2007) to time 1 (2014).

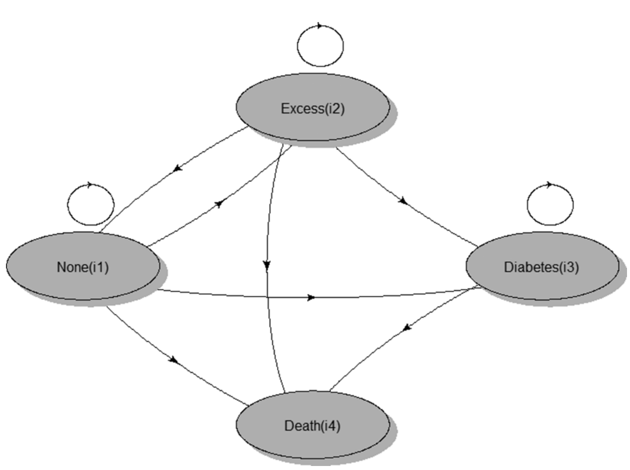

Fig. 1 Transition probability diagram from health status in time 0 to time 1

The transition probability from state i at time 0 to state j at time 1 is illustrated in the following function. The vector x contains the values of the covariates in the regression model, i represents an individual's previous health state at time 0 and, and j is the current health state at time 1. Then k from 1 to L represents any possible transition. Covariates in the regression model include sex, age at time 1 and individual's highest education level (no education, primary, secondary and tertiary). Separate multinominal logit models by initial health state at time 0 are used to estimate the probability of transitioning from the initial state at time 0 to other states (neither overweight nor diabetic, overweight without diabetes, diagnosed with diabetes or death). Transition probabilities are estimated over a five-year interval.

$$\Pr\left(y_1 = j | y_0 = i\right) = \frac{e^{\beta_{ij} X}}{\sum_{k=1}^{L} e^{\beta_{ik} X}}$$

Figure 2 illustrates the diagram of the transition probabilities for males and females based on the initial health state at time 0 to the state at time 1. To simplify presentation, Fig. 2 only shows the transition probabilities for most educated (tertiary) and no education groups. The figure demonstrates that the transition probabilities into having excess body weight and diabetes are higher among people with tertiary education than none-educated group. However, the transition probabilities to mortality are consistently higher among non-educated group compared to people with tertiary education for regardless the initial health state.

The second input is the prevalences of our three modelled states ("not excess weight or diabetic", "excess weight nondiabetic", and "diabetic") in the population. Prevalences of these three health states are calculated by five-year age groups, sex, and education level. We estimate prevalences for these health states for 2007, 2013, and 2018 using the following function.

$$Prevalence_{(state\ i\ by\ age;sex;edu)} = \frac{Total\ cases_{\ (state\ i\ by\ age;sex;edu)}}{Total\ population_{\ (by\ age;sex;edu)}} \times 100\%$$

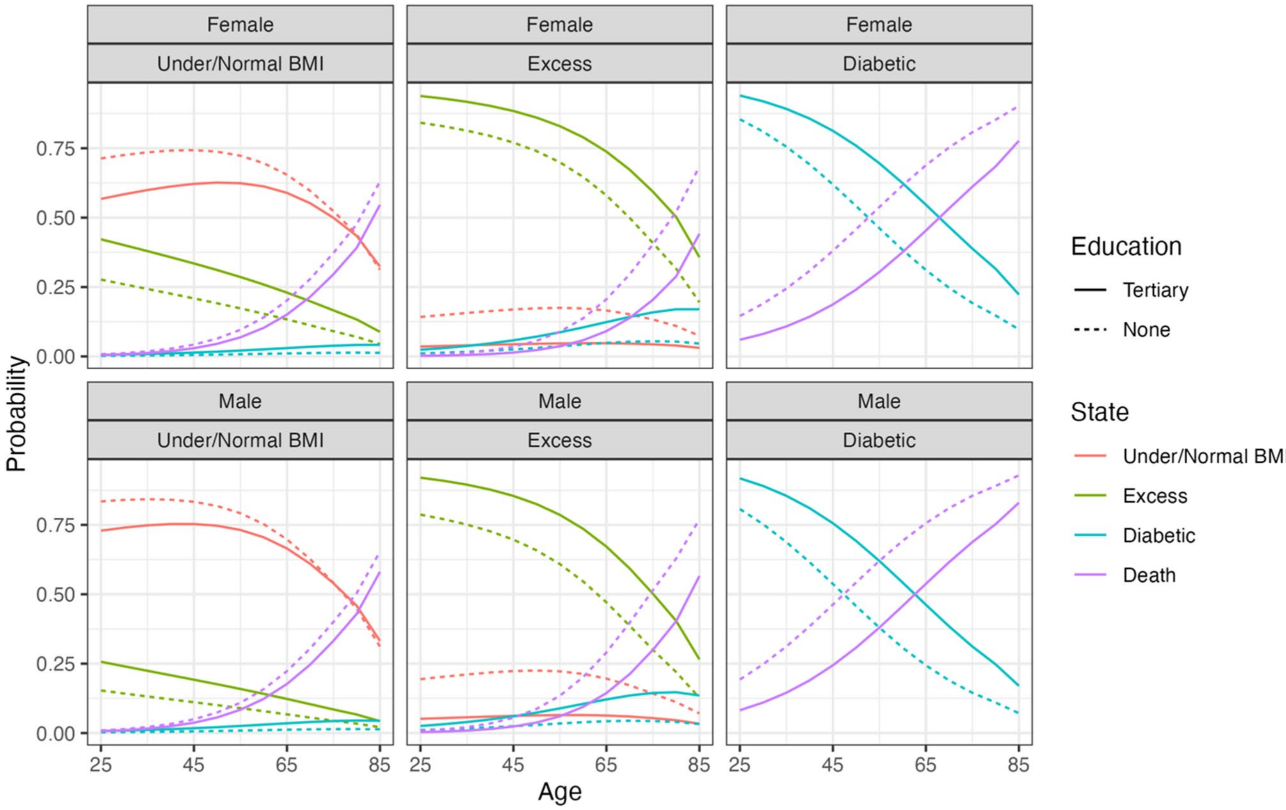

Fig. 2 Prevalence of overweight and diabetes based on Risksesdas

Probability of undiagnosed diabetes

Considering the large proportion of the population with undiagnosed diabetes, our projection adjusts for the probability of undiagnosed diabetes. This probability is derived from IFLS in 2014 that collect both self-reported diabetes and HbA1c values from dried blood spots. Using information HbA1c values for diabetes diagnosis from IFLS, we estimate the probability of undiagnosed diabetes among "neither overweight nor diabetic" and "overweight without diabetes" groups by age, sex and education level. The probability of undiagnosed diabetes is estimated using a probit model based on the 4,988 individuals who were selected for the dried blood test sample and who had never been diagnosed with diabetes (see appendix figure S1 for sample selection). The probability of undiagnosed diabetes in the population is a function of health status at time 1 (neither overweight nor diabetic, or overweight without diabetes based on self-reported diabetes), age, sex, and education level.

$$\begin{aligned}&\text{logit}(P(undiagnosed\ diabetes|\mathbf{X})\\&= State + Age + Sex + Education\ level\end{aligned}$$

Projections of diabetes

We employ a cohort component model with microsimulation to project the population forward. Our initial population data comes from the Wittgenstein Centre Human Capital Data Explorer version WIC2018 v2 estimates for 2010, covering age groups from 25 to 29 to 85+. Using prevalence rates calculated from 2007 survey data (the closest available to 2010), we stratify this initial population by health status within each age group and education level. Starting with this state-, education-, age and sex-specific baseline population, we apply transition probabilities in a microsimulation framework to project the population forward in five-year intervals. This process is repeated using the same transition probabilities for each subsequent projection period until 2060. For the 85 + age group, we apply the transition probabilities three times to extend projections up to age 100+.

To account for population dynamics over time, we incorporate new cohorts entering the 25–29 age group in each projection period. For instance, in 2015, we introduce the 25–29 age group using the Wittgenstein Centre Human Capital Data Explorer version WIC2018 v2 education-specific population estimates for that year. We then disaggregate this group by health status based on 2013 prevalence data. For all periods after 2015, we apply the 2018 prevalence rates to simulate the future population with status quo. The same cohort component model with microsimulation is applied to these future incoming cohorts, projecting them forward alongside existing cohorts until 2060. This approach allows us to maintain a comprehensive view of the population as it ages and as new cohorts enter the model.

Following the projection, we implement an adjustment to account for underreporting in self-reported diabetes cases. This adjustment is crucial for improving the accuracy of our diabetes prevalence estimates. We apply a probability of undiagnosed diabetes given age, sex, education level, and health status to the respective projected population without diabetes. The estimated number of undiagnosed cases is then added to the diabetes group and subtracted from the non-diabetic group, maintaining the overall population total while providing a more realistic distribution of diabetes prevalence.

Results

Figure 3 illustrates the projected burden of diabetes in Indonesia from 2010 until 2060. The black line in Fig. 3 shows the trend of diabetes prevalence without taking account differential in risk of excess weight and diabetes by education level and the change in population education structure over time. The prevalence of diabetes was estimated at 1.2% in 2010 and was expected to be 6.7% by 2060, if the prevalence of diabetes observed in 2018 and transition probabilities continued into the future. The red line presents the scenario additionally incorporating shifts in educational composition. This projection shows a larger increase in diabetes prevalence in the future after taking account the changes in education levels within the population.

Acknowledging the substantial prevalence of undiagnosed diabetes within the population, we adjusted the projection by presuming that the current proportion of undiagnosed diabetes will persist into the future (Fig. 4). The figure illustrates the distribution of the population by health status before (panel a) and after adjusting for diabetes based on HbA1c diagnosis (panel b). The adjustment revealed a significant increase in the proportion of people living with diabetes, largely due to the contributions from overweight individuals who were previously undiagnosed.

Figure 5 shows that diabetes prevalence is expected to grow from 7.8% in 2010 to 16.7% by 2060 after the adjustment (blue line). The estimation from our diabetes projection model is very close with the observed diabetes prevalences using blood test from Indonesia National Health Survey (Riskesdas) from 2013 to 2023. The prevalence of diabetes in the population aged 15 years and older, based on blood tests conducted through national health surveys, was 6.9% in 2013, 10.9% in 2018 and 11.7% in 2023 [36, 37]. The projected prevalence of diabetes among those aged 25 and older, according to our model, is estimated to be 9.6% in 2015, 11.0% in 2020, and 12.1% in 2025.

Figure 6 illustrates estimates of the trend of diabetes in coming years by education level based on the pattern of self-reported diabetes (red line) and after adjusting for undiagnosed diabetes (blue line). The most rapid increase in prevalence after the adjustment is estimated to be among people with only primary education (from

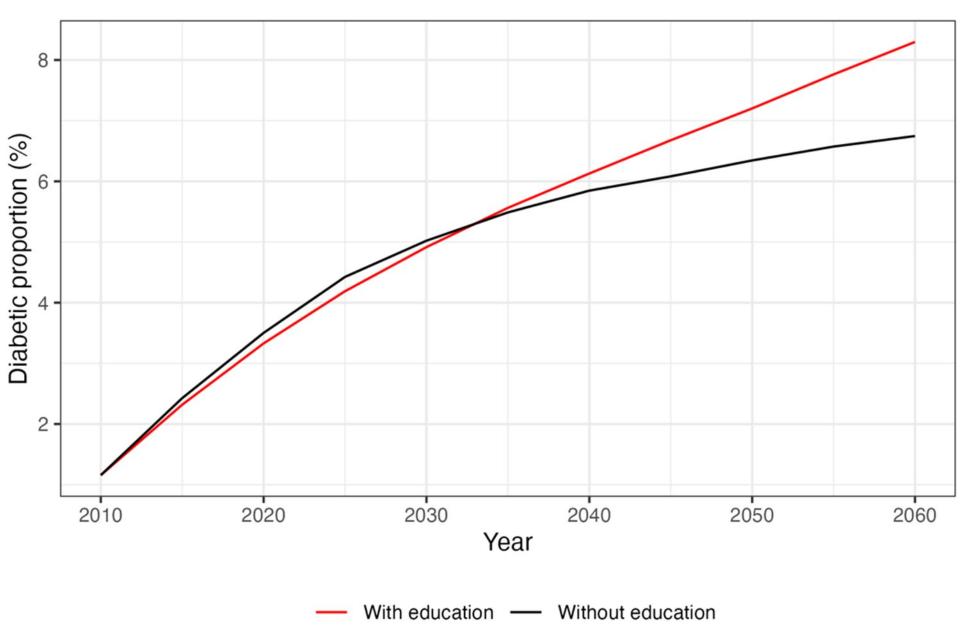

Fig. 3 Prevalence of self-reported diabetes and the projections taking account of population education structure and without education

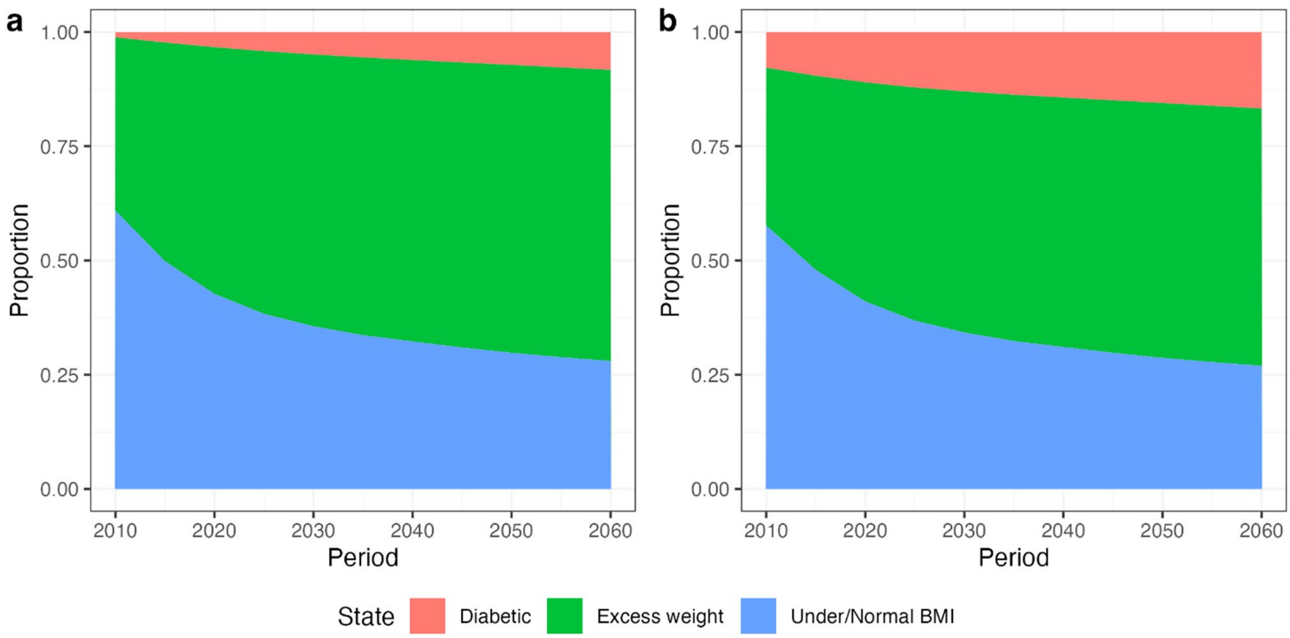

Fig. 4 The proportion of under/normal BMI, excess weight and diabetes, (**a**) before adjustment for undiagnosed diabetes, and (**b**) after adjustment for undiagnosed diabetes

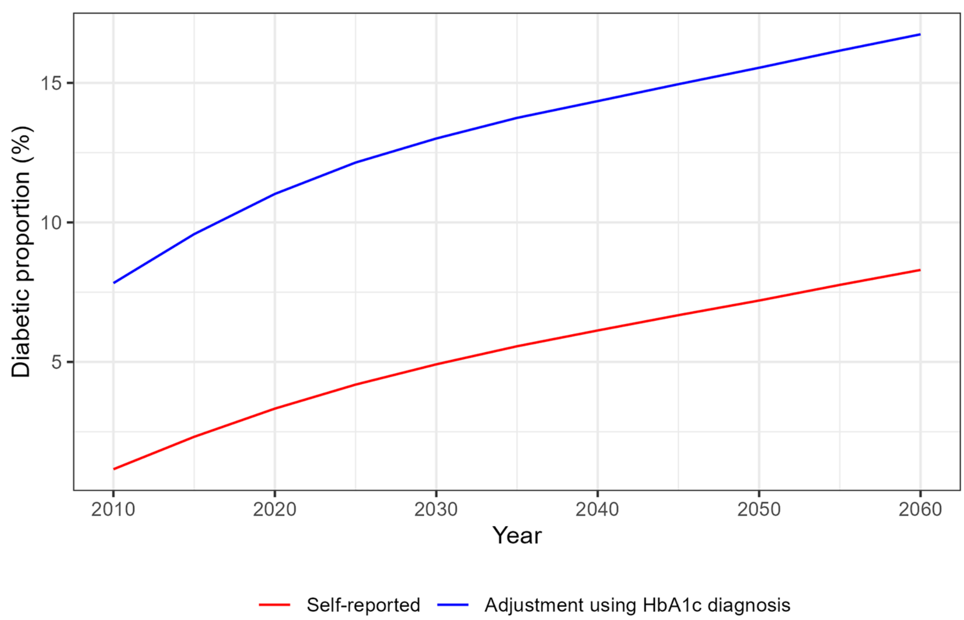

Fig. 5 Prevalence of diagnosed diabetes and the projection taking account of population education structure using self-reported diabetes and after adjustment undiagnosed diabetes based on HbA1c diagnosis

7.8% in 2010 to 22.0% in 2060), while other groups show slower, but still substantial, increases. Given the increase in diabetes prevalence over time, Fig. 6 also demonstrates that there is substantial educational patterning of diabetes underdiagnosis, as the gap between self-reported and adjusted diabetes is substantially larger among less educated groups.

Figure 7 illustrates the increasing burden of excess weight and diabetes in the country from 2010 to 2060. The prevalence of excess body weight rises steadily over time, with earlier onset observed among younger birth cohorts. This highlights the growing number of individuals at risk of developing type 2 diabetes. Notably, the onset of diabetes is projected to occur at an earlier age, with the number of affected individuals increasing as they age, paralleling the rising prevalence of excess body weight in the population. Additionally, individuals living with diabetes are expected to have longer lifespans,

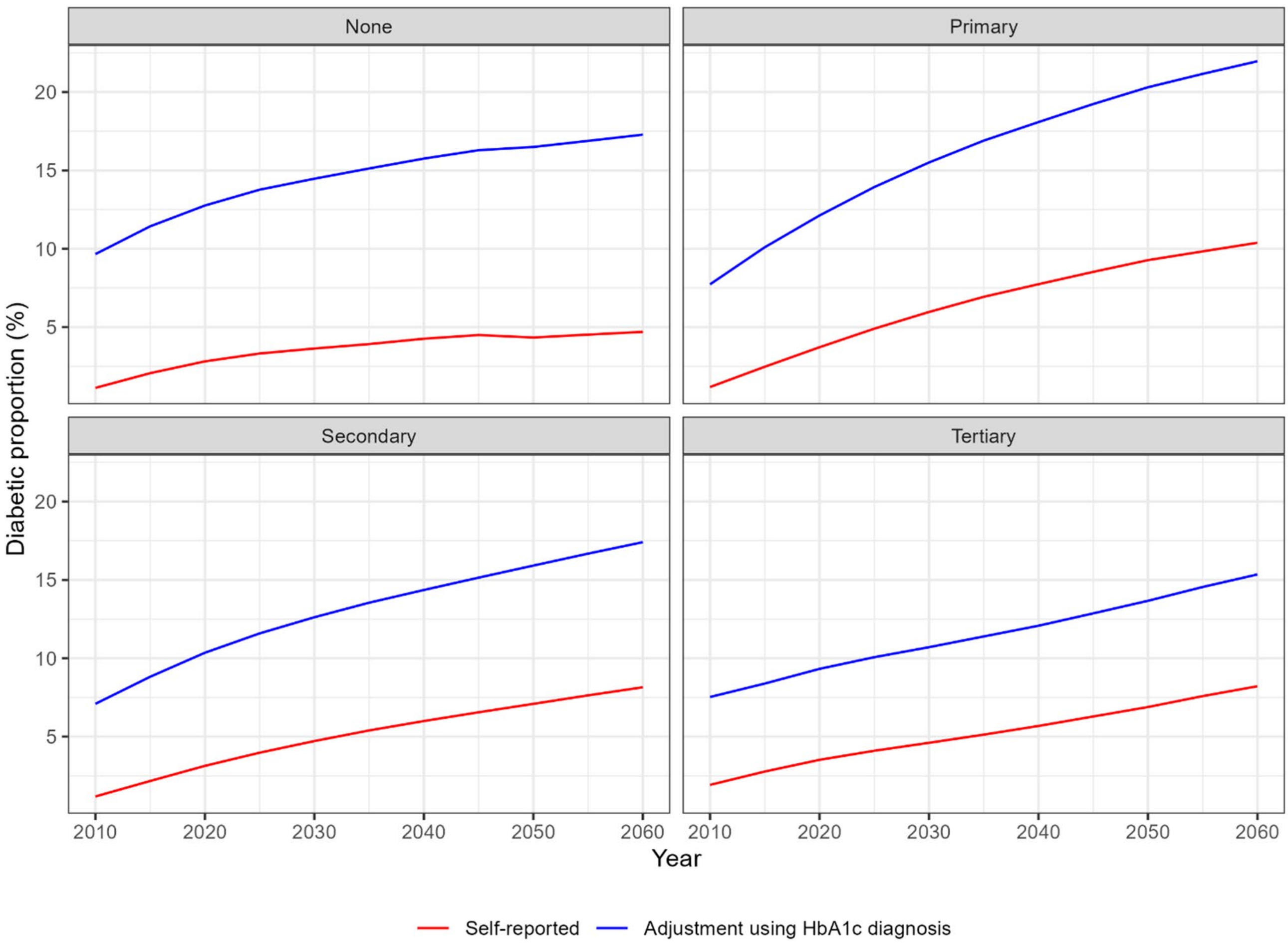

Fig. 6 Prevalence of diabetes and the projection by education level comparing before and after adjustment undiagnosed diabetes

contributing to a higher prevalence of diabetes among older age groups.

Discussion and conclusion

In this study, we present the initial estimates of the future prevalence of excess body weight and diabetes in Indonesia that account for the evolving educational composition of the nation. Our findings demonstrate that incorporating cohort changes in educational attainment into projections of future health status in Indonesia yields significant variations in the overall projected future burden of diabetes and overweight. This analysis provides valuable insights into the relationship between educational attainment and key population health outcomes. In summary, our results suggest that research focused on projecting and comprehending the future burden of health conditions would greatly benefit from incorporating educational attainment as an additional dimension of population composition, particularly in light of the rapid changes in educational attainment across cohorts in many LMICs.

Indonesia's population is set to experience a substantial burden of diabetes in the coming decades, resulting from both demographic aging and an increasing prevalence of overweight and obesity. Indeed, our projections indicate that by 2050, less than 30% of Indonesia's population will be within the "normal" body mass index (BMI) range and without diabetes, while over 15% of the population aged 25 and above will be diagnosed with diabetes. This burden of excess weight and metabolic disorders poses a substantial risk to overall population health in the country. However, our findings, and other recent evidence, suggest that diabetes self-knowledge is poor, and fewer than a quarter of individuals with diabetes were currently receiving treatment [38]. These low rates of linkage to care are problematic in light of the projected rise in diabetes prevalence in Indonesia. In addition, current levels of health-care provider knowledge about diabetes, and effective management strategies, is quite low in Indonesia [39]. As the current levels of diabetes in Indonesia already seem to be stressing the health system, the projected rise in prevalence will require a substantial

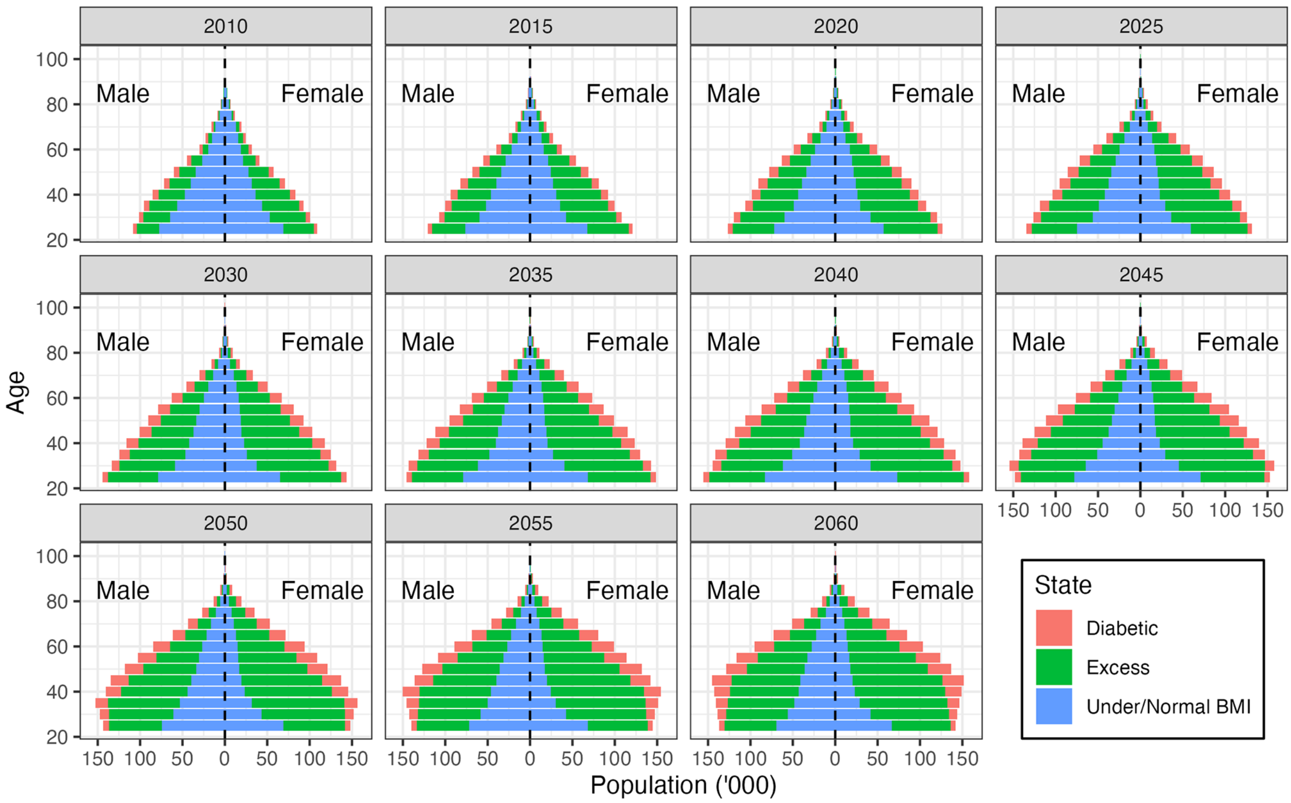

Fig. 7 Projection the number of male and female by health status from 2010–2060

overhaul of current strategies for management and treatment of diabetes.

Our findings suggest that increased educational attainment, and particularly increased prevalence of tertiary education, appears to lead to a slower rise in diabetes prevalence. As the educational composition of the Indonesian population changes over our projection period, this moderating effect leads to a substantially different future burden of diabetes as compared to scenarios which do not take education into account. However, the protective effect of increased tertiary education across successive cohorts is to some extent offset by higher rates of increase among those with only primary schooling, even as this group is projected to shrink over time.

Understanding this complex interplay between diabetes risk and educational attainment is also crucial for gaining insight into the future of health inequalities in this context. Our findings suggest that lower educated individuals are both less likely to know their diabetes status, and more likely to actually be diabetic, as compared to those with higher levels of education. These social inequalities in both diabetes prevalence and self-knowledge are of substantial importance, as they may lead to less educated individuals being substantially disadvantaged in terms of accessing appropriate care for their diabetes.

Policy implications

Combined, these future trends highlight that health care systems in Indonesia will need to work to reorient towards caring for complex non-communicable diseases. Although our analyses focused primarily on the burden of diabetes in the country, the rising trends in overweight/obesity suggest that many other cardiometabolic and cardiovascular conditions may also see increases in coming decades. In addition, our findings highlight key social inequalities in both diabetes self-knowledge and biomarker-assessed diabetes prevalence across educational groups. Closing these health knowledge gaps is crucial for improving population health, especially for diseases like diabetes which are much more manageable when identified at an early stage. Our projections offer insights that can help to improve population health by more effectively targeting these groups, such as priority budgeting in healthcare and education/literacy-sensitive interventions for effective obesity management and diabetes prevention among lower-educated individuals.

Strengths and limitations

One of the main strengths of our analyses was our integration of multiple data sources to project diabetes burden in Indonesia. The use of longitudinal data in this study allowed for a more reliable projection of the burden of excess weight and diabetes in the country, as it was based on individual health transitions over the observed time period. However, adjustments for undiagnosed diabetes using dried blood tests from the longitudinal data may have resulted in underestimation, as there was no baseline measurement of diabetes status at the initial stage. Nevertheless, our estimated prevalence of diabetes adjusted for undiagnosed cases based on dried blood tests closely align with observed diabetes prevalence from blood tests conducted in the national health survey.

In conclusion, integrating the educational composition of the population into projections of excess body weight and diabetes burden offers important insights into how social disparities in diabetes can impact population health over time. This information can guide policy decisions, assisting in the prioritisation of healthcare funding, targeted prevention programs, and diabetes treatment for high-risk groups according to their educational status.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12963-025-00372-2.

Supplementary Material 1

Author contributions

LL co-developed the research plan, acquired the data, conducted statistical analysis, and wrote the first draft of the manuscript. The TS contributed to conducting the analysis and drafting the manuscript. CFP co-developed the research plan, provided feedback on analysis, acquired funding, and contributed to drafting the manuscript. All authors reviewed the manuscript and approved of submission.

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Data availability

The IFLS datasets used in these analysis are publicly available from the RAND corporation IFLS repository at https://www.rand.org/well-being/social-and-behavioral-policy/data/FLS/IFLS.html. The Indonesian National Health Survey (Riskesdas) is publicly available and can be requested from the Indonesian Ministry of Health at https://layanandata.kemkes.go.id. The population baseline for this research can be obtained from the Wittgenstein Centre Human Capital Data Explorer version WIC2018 v2, which is publicly available and accessible at https://dataexplorer.wittgensteincentre.org/wcde-v2/.

Declarations

Ethical approval

The Indonesian Family Life Surveys were reviewed and approved by Institutional Review Boards (IRBs) in the United States at RAND and in Indonesia by University of Indonesia for waves 1 and 2, and University of Gadjah Mada for waves 3 to 5. Written informed consent was obtained from all respondents prior to data collection. The analysis in this study has received ethics approval from the Humanities and Social Sciences DERC at The Australian National University with the protocol number: 2022/004.

Competing interests

The authors declare no competing interests.

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